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“Fault Detection and Identification for Maintenance Management”

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Fault Detection and Identification for Maintenance Management

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Abstract

Photovoltaic solar energy is increasing the energy production due to the technological advances, together to the initial investment reduction. Solar farms are being installed with larger production capacity, improving the technical challenge for developing correct and efficient maintenance management. The photovoltaic maintenance management requires to increase the reliability and reduce the operating costs. The photovoltaic panels inspection with unmanned aerial vehicles is an efficient condition monitoring technique, analyzing large areas and obtaining accurate thermographic images. Due to the large amount of data, it is necessary the use of image processing algorithms for automatic identification of faults. Despite these advances, it is required the identification of the type and the importance of the fault. This information will be used by the plant operators for developing efficient maintenance management plans. The novelty developed in this work is a robust decision system for photovoltaic maintenance management, based on the combination of image processing for fault detection and statistic techniques. The first phase of the methodology is the extraction of interest areas or possible faults with neural networks trained for this purpose. The second phase develops the statistical analysis of the radiometric data of the area detected as possible fault with neural network. The radiometry data of these areas will be analyzed with statistic models with the aim of detecting patterns for detect identification and quantification. A real case study of a solar plant is presented, and the results obtained with this methodology provide the positioning and importance of each defect, probing the strength of the method.

Key Words: Infrared Thermography, Solar Photovoltaic Energy, Condition Monitoring System, Remotely Piloted Aircraft, Neural Network, Photovoltaic Management.

1 Introduction

The worldwide electricity demand is increasing every year and the conventional energy sources are causing an elevated environmental impact. The electric generation from renewable energies is fundamental for reducing gas emissions, getting the zero-emission agreement in 2050 [1]. Photovoltaic (PV) solar energy is one of the most significant renewable energy sources, and this technology has a fundamental role in the energy transition. The solar energy is growing due to the reduction of panel prices, the development of novel energy storage solutions and the increment of the energy production reliability [2]. In 2018 was installed 102,4 GW, and the previsions for 2019 are around 114,5GW. The PV solar contribution to global electricity generation was increased in more than 2%. Asia continues leading the global market, mainly in China and Japan, followed by the United States [3]. It is expected to rise to 180GW in a global medium scenario in 2023, see Figure 1.

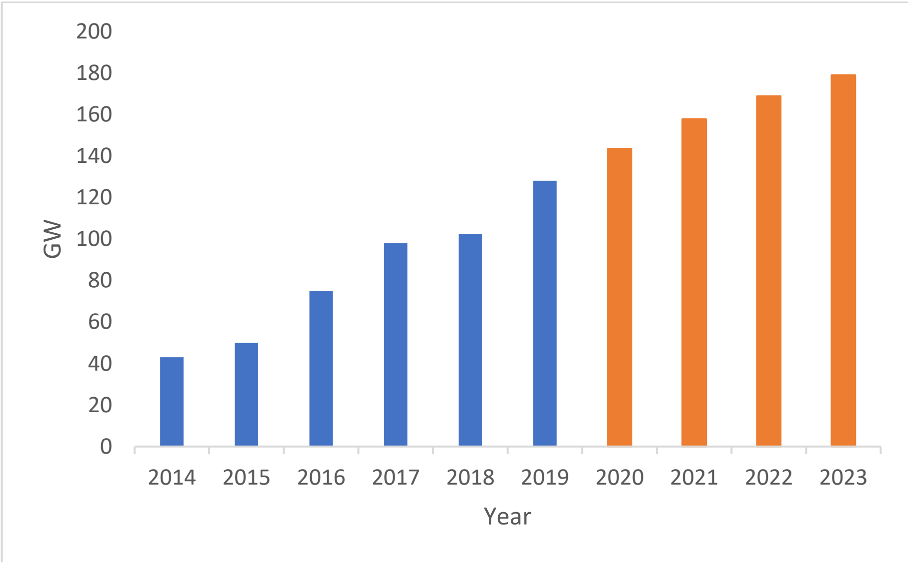


Figure 1: World annual solar PV market and forecasting for 2019-2023 [3]

Due to advances in manufacturing process, PV systems have increased its competitiveness. The efficient of silicon cells is between 5-19% although it is still low in comparison with other renewable energies [4]. The productivity of the PV farms is based on the maintenance costs, initial investment, the lifetime, the financing and loan conditions. The reduction of the operation and maintenance (O&M) costs is required to reach the competitiveness [5], and to ensure the economic feasibility of the PV solar plant [6]. The current size of solar farms is larger every year, and an efficient maintenance management plan is required for ensuring the reliability [7].

The PV performance in long-term is affected by different faults that reduce the energy production of the plant. The adverse environment conditions of the PV farms reduce the crystalline-Si modules performance. PV panels present faults when the modules are working in unusual conditions. The main PV failures are hot spots, module open circuited, short circuited, delaminated, broken or fault cell, shadowing effect, bubble, presence of dust and open-circuit bypass diode [8]. Electrical failures or presence of dust in the panels produce variations in the superficial temperature and reductions in the generated power [9]. The deposition of dust or dirt is a critical problem for the industry, since it varies the solar radiation angle reducing the electricity production. The effect of dust on PV performance has been studied in different countries, and the percentage depends on the time period and the particle size, determining that finer particles have more influence in the efficiency mitigation. The hot spot detection is the main goal of the maintenance industry to reduce the downtimes and identify faults before the increment of the severity.

Current condition monitoring systems (CMS) employ different sensors and data acquisition systems, evaluating different parameters of the PV panel and energy production for further analysis [10]. Supervisory Control and Data Acquisition (SCADA) system provides suitable data about the real state of the system for improving the maintenance management plans [11]. SCADA system in PV farms uses different sensors and subsystems for monitoring the electrical production to the panels. With this monitoring technique, it is possible to identify certain faults, but the state of the panel surface it is no considered in the analysis. Between a 33-43% of the PV module failures are located in the cells and glass of the PV module [12], therefore, it is needed advanced CMS for inspecting superficial faults. Diagnostic algorithms use the data acquired for obtaining the fundamental information, e.g. electric generation simulations tests comparing the model with the real situation [13], neural networks [14,15] and fuzzy logic [16].

The infrared (IR) thermography is one of the most suitable technique for inspecting solar farms and detect heat patterns, preventing the development of failures [17]. The thermography is a non-destructive technique employed in the industry based on the detection of the infrared energy, invisible for the human view. This energy is emitted by the surface of a body. This information is transformed into thermal values. The infrared cameras capture radiometric thermal images, or thermograms, where the temperature values are displayed with different colour scale. This type of cameras can also provide the temperature in each pixel of the image. IR is applied in several industrial fields, such as civil buildings, manufacturing and welding inspection, among others, due to its easy implementation, non-contact technique and the possibility of extract information in thermal images and data from radiometry. Despite these advantages, the inspection rate is not enough for the current plant requirements. The thermography analysis is developed manually by technicians with elevated costs and time as a result of the larger size of current solar farms. This technique combined with unmanned aerial vehicles (UAV), or drones, makes possible to cover more areas, ensuring the reliability and efficiency of the measurement process. UAVs have a great establishment in several industrial fields, highlighting PV maintenance, due to its capacity of covering large areas, carrying different CMSs, data capture automatization, favourable legislation and flexibility in control and design. Different researches are focused on novel CMS in UAVs [18], increasing the efficiency of aerial inspections. Due to the amount of data generated in the inspection of large solar farms, novel digital technologies based on big data analysis are needed for post-processing phases [19]. The neural networks have expanded its range of applications in the last 15 years, being applicated in complex and nonlinear problems [20]. The Region-based Convolutional Neural Network (R-CNN) can learn from training using examples for pattern identification in several application fields. Traditional computational activities are based on pre-stablished rules [21], but R-CNN can work with problems with discontinuous data. With this algorithm is possible to detect objects with great accuracy and classifying the type of detected object. The training with image level identification by the user is fundamental for adapting the R-CNN to the required detection [22]. J. Muñoz et al. studied the risk of hot spots, that can cause irreversible damage in modules, appearing in PV solar cells and also in resistive solder bonds [23]. The method presented in this paper allows to detect and located faults automatically. Literature shows similar techniques to locate faults. Similar works can be found in the literature [24], however, they do not employ the region- R-CNN. Most of the works about thermography inspection of PV solar panels focus on the analysis of individual panels. In those works, different methods were applied to demonstrate the capabilities of thermography, for example, studying the efficiency of the panel, detecting relative hot regions in panels or identifying general faults in PV modules [25].

Several authors present analogous methodologies for fault detection in PV panels. Kim et al. [26] analyse the thermal images taken by a thermal camera and a UAV, and they develop an image segmentation considering only the area of the panel. The PV panels are simulated as polygons and the information outside these areas is not considered. The statistical analysis is focused in all the panel area, losing efficiency and increasing the computational load. Kaplani [27] analyses the degradation effect with I-V curve, IR thermography and an algorithm is developed for detecting discoloration in PV cells. Huerta et al. [28] proposes a recurrent convolutional neural network for the identification of hot spots. Segovia et al [29] developed a real case study based of simulating dust in PV panel and analyse the thermal data. The regions of interest (ROI), where it is possible to find faults, are selected manually. However, the proposed method is employed in a real PV solar plant, where many panels can be analyzed together. Therefore, the main contribution of this paper with respect to the literature is the development of an intelligent algorithm that detects hot areas of solar panels. The algorithm is tested in a real PV solar farm.

The novelties proposed in this article are resumed in the following points:

- The implantation of Neural Network as solution for hot spot identification in the solar maintenance using aerial images taken by a UAV. The image identification of the hot spot is combined with statistical analysis of the data. This methodology allows the fault detection and identification by thermal patterns. The union between image detection and statistical analysis allows the reliability of the fault detection and the efficiency of the numerical analysis.
- The analysis with basic statistics reduces the computational costs and allows the fault identification and classification regarding on the severity and importance.

2 R-CNN and statistical analysis: real case study

The methodology proposed in this work uses the information extracted from the image identification algorithm as input for the analysis of the radiometric data. This approach combines image fault detection and radiometric analysis of the detected fault. For this reason, this method is only applied in radiometry thermographic images, where it is possible to detect the accurate thermal value in each pixel. The first phase is based on the image fault identification by means of R-CNN. The neural network is trained for identifying hot spots in the panels, and the pixel location of the identified fault is storage for further analysis. The GPS positioning is storage for further location of the failures. In the second phase, the pixels with detected failures are presented and the thermal values are analysed with different statistic tools for extracting patterns. This process is automatic, and the user only have to upload the information to the system and the results will be generated. Figure 2 shows a diagram of the process.

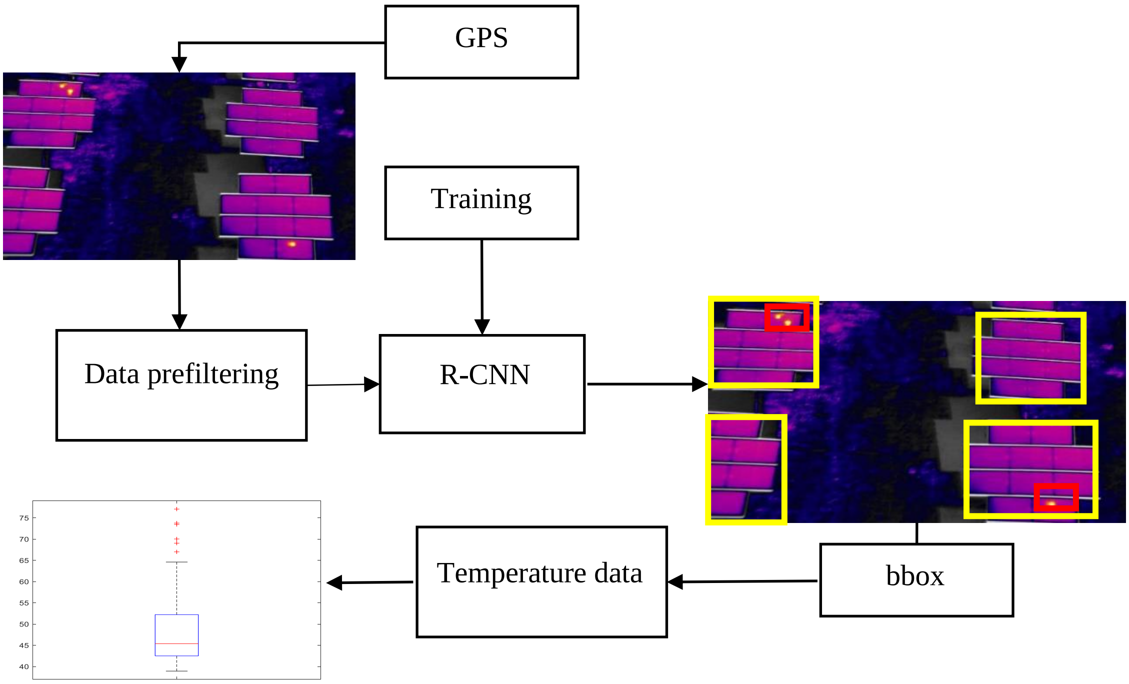


Figure 2: Methodology diagram

The design and development of novel neural network is not the main objective of this paper. The R-CNN developed by Huerta et al. [28] to validate the approach presented in this paper. The fault detection by neural network provides three variables about the failure: bbox, score and label. The score variable shows the confident level of the results. In this case, it is ensured that the results will have a 70% of confident. The **bbox** matrix has the information about the pixel location of the fault in the thermogram. Label is the categorial array assigned to the bounding boxes and, in this case, classify in panel or fault. The fault is only detectable if it is in the area detected as panel, in order to ensure that no false failures are considered. The information of **bbox** will be used in the second phase of the analysis. In this phase, the thermal information of the coordinates given by **bbox** is storage. It is pretended to use basic configurations in order to reduce the computational load of all the operations and develop the statistical analysis. The mean value, variance and standard deviation are common statistical variables employed in may application fields and in the image distribution [30]. The application of boxplot analysis in the performing of temperature fluctuation is a fundamental tool to detect graphically thermal patterns.

The case study presented in this work is based on the aerial thermographic inspection developed in a real solar farm in 2017. Figure 3 shows a thermogram acquired by a UAV and a thermographic camera. The images are prefiltered and orientated for the suitable application of the R-CNN. The pixel data about the location of panels and faults identified by the neural network is applied in the boxplot graphic.

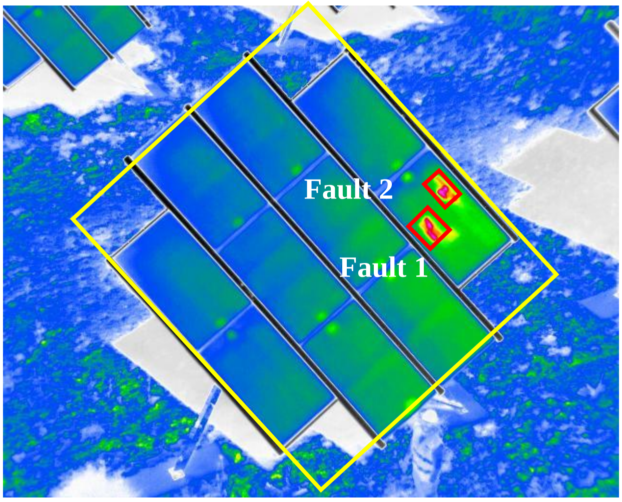


Figure 3: Thermogram with detected failures.

Figure 4 compares the distribution of the temperature fluctuation of the faults showed in Figure 3. Both thermal patterns present the same distribution due to the similarities between failures. The number of outliers and the values are quantified to determine the importance of the faults. Fault showed in Figure 4.b presents high number of outliers and this fault is considered with more importance than the fault presented in Figure 4.a.

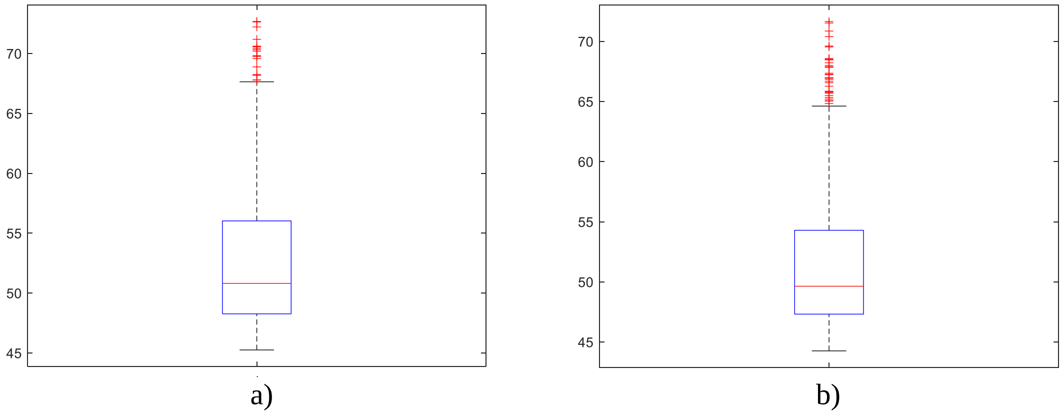
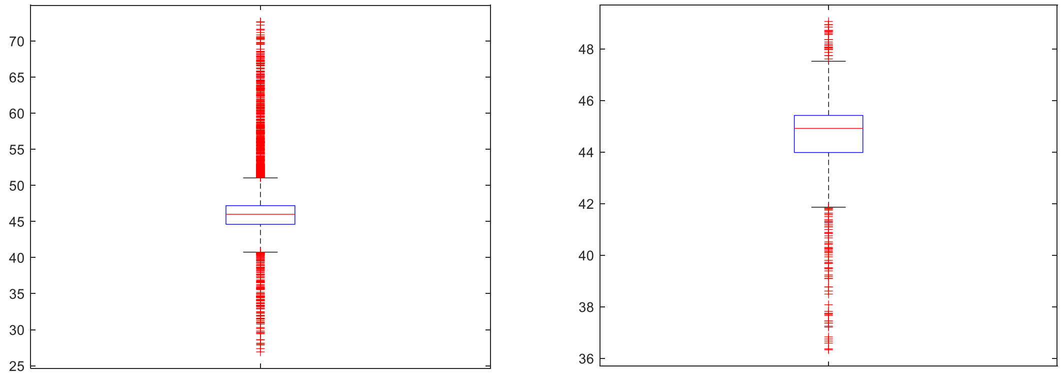


Figure 4: a) Fault 1. **b)** Fault 2

The comparison between panels with faults and panels with no faults is presented in Figure 5. The distribution of the panel with faults in the higher positions proves the presence of several pixels with overheat. The outliers in the bottom part of the diagram are produced by the difference between the square form of the R-CNN detector and the form of this specific type of panel, capturing data of the ground. Despite this effect, the information about the real state of the panel is acquired and it is possible to identify critical panels regarding on the number of outside outliers.



a) b)

Figure 5: a) Panel with faults. **b)** Panel with no fault

Figure 6 shows the same panel displayed in the Figure 3 at higher altitude. This image allows the validation of the method at different altitude. In this case, other PV panel with faults is detected and the results are compared.

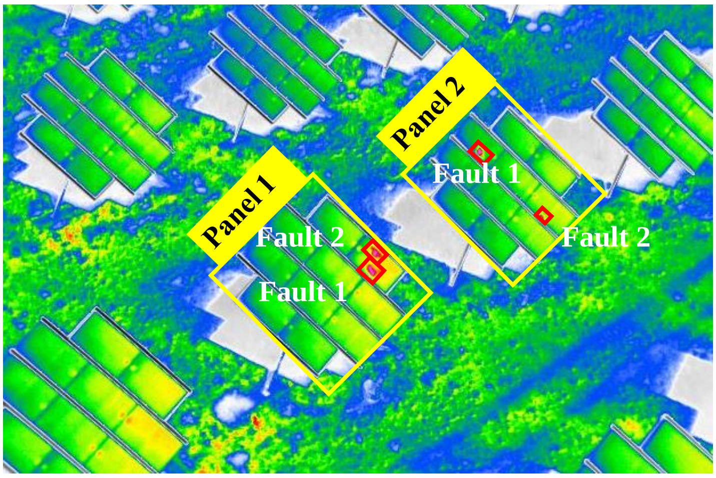
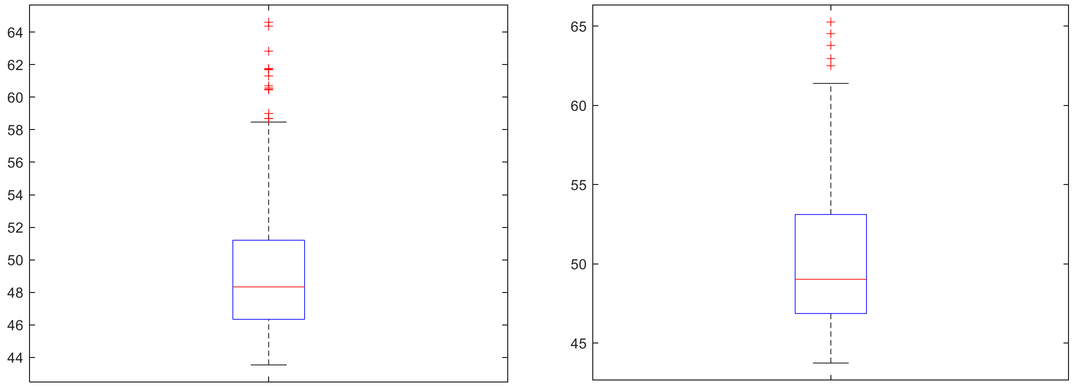


Figure 6: Thermogram with different panels affected

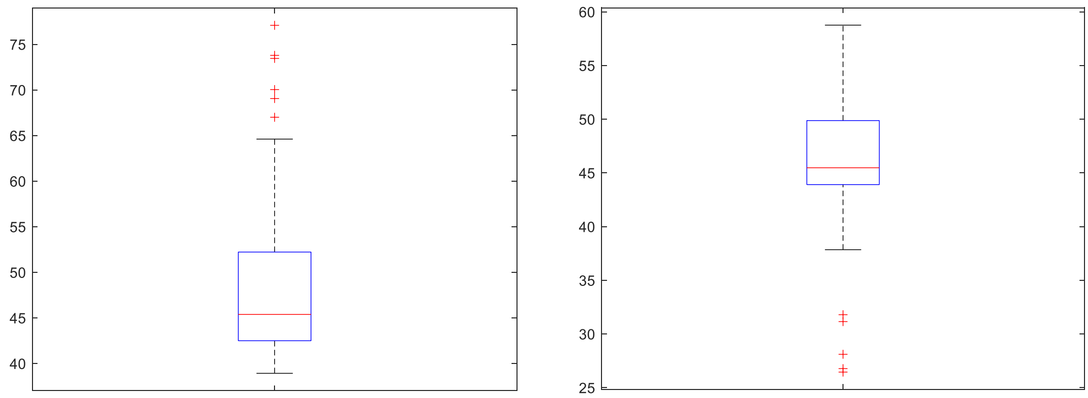
Figure 7 evaluates the boxplots of the PV panel 1 faults. The number of outliers is reduced in comparison with Figure 4 because of the higher altitude decrease the regions of interest size and the number of detected pixels.



a) b)

Figure 7: a) Panel 1 Fault 1. **b)** Panel 1 Fault 2

Figure 8 shows the hot spots in the other PV module. The fault 2 has outliers with temperature values lower than Q1 due to the area selected by the algorithm. The fault is close to the panel limit made with aluminium and the temperature values are reduced because of reduced emissivity of the aluminium. Despite this issue, it is possible to identify the failure. In this scenario, fault 1 can be detected clearly than fault 2.



a) b)

Figure 8: a) Panel 2 Fault 1. **b)** Panel 2 Fault 2

Figure 9 compares the three panels affected. The PV panel with no faults in Figure 9.a shows outliers with lower values than the median due to the square form of the detector considering the values behind the panel. Boxplots in Figure 9.b-9c has similar fluctuation but the fault in Figure9.c has more relevance since a greater number of outliers are detected and therefore, i.e. more area of the PV panel is overheated.

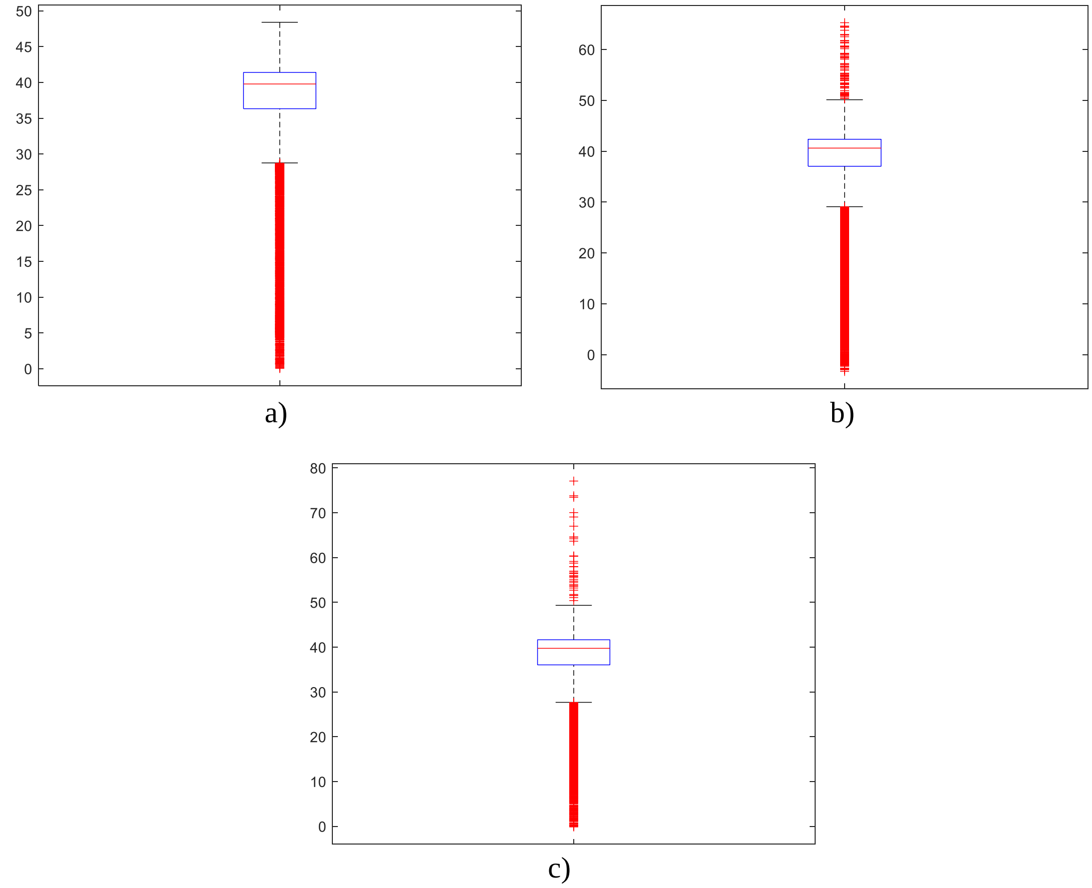


Figure 9: a) Panel, free-fault. **b)** Panel 2, fault 1. **c)** Panel 3, fault 2.

3 Conclusions

Photovoltaic solar energy maintenance is required to reach the feasibility of the solar plants. Novel condition monitoring systems are necessary for fault detection and diagnosis. Aerial thermography is a novel technique based on the analysis of images done by a thermographic camera embedded in an unmanned automatic vehicle. The volume of the data generated implies robust and complex algorithms. This paper proposes an algorithm combining neural network for detecting the fault positioning together with statistical analysis of the radiometric data for quantifying the importance of the fault. The methodology is tested using real thermograms, and different faults are analysed and quantified using the algorithm. The results show the efficiency and accuracy of this approach.

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